
Semantic Graph for Zero-Shot Learning

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Abstract

Zero-shot learning aims to classify visual objects without any training data via knowledge transfer between seen and unseen classes. This is typically achieved by exploring a semantic embedding space where the seen and unseen classes can be related. Previous works differ in what embedding space is used and how different classes and a test image can be related. In this paper, we utilize the annotation-free semantic word space for the former and focus on solving the latter issue of modeling relatedness. Specifically, in contrast to previous work which ignores the semantic relationships between seen classes and focus merely on those between seen and unseen classes, in this paper a novel approach based on a semantic graph is proposed to represent the relationships between all the seen and unseen class in a semantic word space. Based on this semantic graph, we design a special absorbing Markov chain process, in which each unseen class is viewed as an absorbing state. After incorporating one test image into the semantic graph, the absorbing probabilities from the test data to each unseen class can be effectively computed; and zero-shot classification can be achieved by finding the class label with the highest absorbing probability. The proposed model has a closed-form solution which is linear with respect to the number of test images. We demonstrate the effectiveness and computational efficiency of the proposed method over the state-of-the-arts on the AwA (animals with attributes) dataset.

1 Introduction

Zero-shot learning (ZSL) for visual classification has received increasing attentions recently [10, 17, 16, 8, 13]. This is because although virtually unlimited images are available via social media sharing websites such as Flickr, there are still not enough annotated images for building a visual classification model for a large number of visual classes. ZSL aims to imitate human's ability to recognize a new class without even seeing any instance. A human has that ability because he/she is able to make connections between an unseen class with the seen classes based on its semantic description. Similarly a zero-shot learning method for visual classification relies on the existence of a labeled training set of seen classes and the knowledge about how each unseen class is semantically related to the seen classes.

An unseen class can be related to a seen class by representing both in a semantic embedding space [8]. Existing ZSL methods can be categorized by the different embedding spaces deployed. Early works are dominated by semantic attribute based approaches. Visual classes are embedded in to an attribute space by defining an attribute ontology and annotating a binary attribute vector for each class. The similarity between different classes can thus be measured by how many attributes are shared. However, both the ontology and attribute vector for each class need to be manually defined with the latter may have to be annotated at the instance level due to large intra-class variations. This gives poor scalability to these attribute-based approaches [13]. Alternatively, recently embedding based on semantic word space started to gain popularity [8, 13]. Learned from a large language

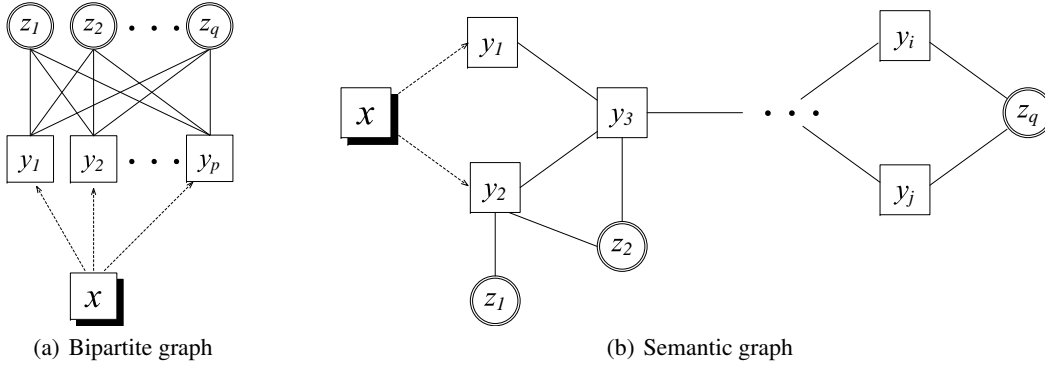


Figure 1: Bipartite graph [17] vs. the proposed semantic graph for zero-shot object classification. An unseen data point is denoted as x ; the i -th seen and unseen classes are denoted as y_i and z_i respectively.

corpus, this embedding space is ‘free’ and applicable to any visual classes [12, 11]. It thus has much better scalability and is the embedding space adopted in this paper.

After choosing an embedding space, the remaining problem for a ZSL approach is to measure the similarity between a test data with each unseen class so that (zero-shot) classification can be performed. Since there is no training data for the unseen classes, such a similarity obviously cannot be computed directly and the training data from the seen classes need to be explored to compute the similarity indirectly. Again, two options are available. In the first option, the seen class data are used to learn a mapping function to map a low-level feature representation of a training image to the semantic space. Such a mapping function is then employed to map a test image belonging a unseen class to the same space where similarity between the data and a class embedding vector can be computed for classification [8]. However, this approach has an intrinsic limitation – the mapping function learned from the seen class may not be suitable for the unseen classes due to the domain shift problem. Rectifying this problem by adapting the mapping function to the unseen classes is also hard as no labeled data is available for those classes. The second option is to avoid the need for mapping a test image into the semantic embedding space. The training data is used in a different way – instead of learning a mapping function from the low-level feature to the semantic embedding space, a n -way probabilistic classifier is learned in the visual feature space. The embedding space is used purely for computing the semantic relatedness [17] between the seen and unseen classes. This semantic relatedness based approach alleviates the domain shift problem and has been empirically shown to be superior to the direct mapping based approach [9, 13]. It is thus the focus of this paper.

In this paper, a novel semantic graph based approach is proposed to model the relatedness between seen and unseen classes. In previous work [17], the relatedness between seen and unseen classes is modeled with a bipartite graph. As shown in Fig. 1(a), in such a graph the relatedness between each unseen class and each seen class is modeled directly in a flat structure, while the relatedness between the seen classes is ignored. This can be viewed as an ‘one step’ exploration in the bipartite graph. In contrast, in this paper, we extend the modeling for semantic relationships from the flat structure to a hierarchical structure and perform a multiple-step exploration. As shown in Fig. 1(b), in our approach, seen and unseen classes will form a semantic graph, in which each seen or unseen class corresponds to a graph node. The semantic graph is constructed as a k -nearest-neighbor (nn) graph. It should be noted that on a semantic graph, the relatedness between seen classes is modeled explicitly; in addition, each unseen class can only connect with seen classes and there is no direct connection among unseen classes. In this way the relatedness between different seen classes are also exploited, making the similarity measure between a test image and each unseen class more robust. Furthermore, compared to the bipartite graph, the k -nn semantic graph can be computed more efficiently. For example, for p seen classes and q unseen classes, the bipartite graph needs to store $O(pq)$ parameters (the weights on the graph edges), while the k -nn semantic graph only needs to store $O(k(p + q))$ parameters.

More specifically, for a test image x , to perform the zero-shot learning, we connect it to the seen class nodes, that is, we incorporate x into the semantic graph. Different with the bipartite graph-based method [17], it is possible that there is no direct connection between the real target unseen class and the seen classes connected by the test image on the semantic graph. Consequently, we have to design a new approach so that if the test image and an unseen class are connected with shorter paths on the semantic graph, the test image should have higher probability to be labeled as that unseen class. For example, in Fig. 1(b), the test image x should have higher probabilities to be classified to unseen class z_1 or z_2 than z_q . To this end, we define a special absorbing Markov chain process on the semantic graph. We view each unseen class node as the absorbing state. Thus, each path that starts from x and terminates at one unseen class will not include other unseen classes. The inner nodes of such kind of paths only include the seen class nodes. The seen class nodes can thus be viewed as the bridge nodes that connect the test image and the unseen classes. The absorbing probabilities from the test image to each unseen class can be effectively computed. Given the predicted absorbing probabilities, we perform zero-shot learning by finding the class label with highest absorbing probability. Moreover, we show that the proposed method has a closed-form solution which is linear with respect to the number of test images.

The main contributions of this work are as follows. First, we propose to use the k -nearest-neighbor semantic graph to model the relatedness among seen and unseen classes. This makes the similarity measure between a test image and unseen classes more robust, and as the number of visual categories increases, compared to bipartite graph, our k -nn semantic graph will be more efficient. Second, we design a special absorbing Markov chain process on the semantic graph and show how to effectively compute the absorbing probabilities from one test image to each of unseen classes. Third, after stacking the absorbing probabilities for each test image together, we provide a zero-shot learning algorithm that has a closed-form solution and is a linear with respect to the number of test images.

The remainder of this paper is organized as follows. After a review of previous work (Section 2), we first introduce our approach (Section 3) and then give experimental results (Section 4). The paper concludes in Section 5.

2 Previous Work

Semantic embedding for ZSL. In most earlier works on zero-shot learning, semantic attributes are employed as the embedding space for knowledge transfer [10, 15, 6, 5, 1]. Most existing studies assume that an exhaustive ontology of attributes has been manually specified at either the class or instance level [10, 18]. However, annotating attributes scales poorly as ontologies tend to be domain specific. For example, birds and trees have very different set of attributes. Some works proposed to automatically learn discriminative visual attributes from data [7, 6]. But this sacrifices the nameability of the embedding space as the discovered attributes may not be semantically meaningful. To overcome this problem, semantic representations that do not rely on an explicit attribute ontology have been proposed [17, 16]. In particular, recently semantic word space has been investigated [14, 19, 8]. A word space is extracted from linguistic knowledge bases e.g. WordNet or Wikipedia by natural language processing models. Instead of manually defining an attribute prototype, a novel target class’ textual name can be projected into this space and then used as the prototype for zero-shot learning. Typically learned from a large corpus covering all English words and bi-grams, this word space can be used for any visual classes without the need for any manual annotation. It is thus much scalable than an attribute embedding space for ZSL. In this work, we choose the word space for its scalability, but our method differs significantly from [14, 19, 8] in how the embedding space is used for knowledge transfer and we show superior performance experimentally (see Section 4).

Knowledge transfer via an embedding space. Given an embedding space, existing approaches differ significantly in how the knowledge is transferred from a labeled training set containing seen classes. Most existing approaches, such as direct attribute prediction (DAP) [10] or its variants [8] take a directly mapping based strategy. Specifically, the training data set is used to learn a mapping function from the low-level feature space to the semantic embedding space. Once learned, the same mapping function is used to map a test image in to the same space where the similarity between the test image to each unseen class semantic vector or prototype can be measured [8]. This strategy however suffers from the mapping domain shift problem mentioned earlier. Alternatively, a semantic relatedness based strategy can be adopted. This involves learning a n -way probabilistic classifier

in the low-level feature space for the training seen classes. Given a test image, the probabilities produced by this classifier for each seen class indicate the visual similarity or relatedness between the test image and the seen classes. This relatedness is then compared with the semantic relatedness between each unseen class and the same seen classes. The test image is then classified according to how the visual similarity and semantic similarity agree. One representative approach following this strategy is Indirect Attribute Prediction (IAP) [9]. It has also been shown that the semantic relatedness does not necessarily come from a semantic embedding space, e.g. it can be computed from hit counts from an image search engine [17]. This indirect semantic relatedness based strategy can be potentially advantageous over the direct mapping based one, as verified by the results in [9, 13]. However, as we analyzed earlier, the existing approaches based on semantic relatedness employ a flat bipartite graph and ignore the important inter-seen-class relatedness. In this work we develop a novel semantic graph based zero-shot learning method and show its advantages over the bipartite graph based methods on both classification performance and computational efficiency.

3 Approach

3.1 Problem Definition

Let $\mathcal{Y} = \{y_1, \dots, y_p\}$ denote the seen classes set and $\mathcal{Z} = \{z_1, \dots, z_q\}$ denote the unseen classes set. Given a training dataset $X_{\mathcal{Y}}$ labeled as $y_j \in \mathcal{Y}$, the goal of zero-shot learning is to learn a classifier $f : X \rightarrow \mathcal{Z}$ even if there is no training data labeled as $z_j \in \mathcal{Z}$.

Taking a semantic relatedness strategy for knowledge transfer, we first utilize the training dataset $X_{\mathcal{Y}}$ to learn a classifier for the seen classes \mathcal{Y} . In this paper, we use the support vector machine (SVM) as the classifier for seen classes. For a test image $x_i \notin X_{\mathcal{Y}}$, the SVM classifier can provide an estimate of the posterior probability $p(y_j|x_i)$ of image x_i belonging to seen class y_j . Let $t_{i,\cdot} = [t_{ij}]_{1 \times p}$ be a row vector with p elements, in which each element $t_{ij} = p(y_j|x_i)$. For a whole test dataset with n images, we will have the matrix $T = [t_{ij}]_{n \times p}$, in which each row corresponds to a test image x_i . T stores the relationship between the test images and the seen classes. It should be noted that although in this work, this relationship is measured by the posterior probability $p(y_j|x_i)$, other ways of computing the relationship between test images and the seen classes can also be adopted.

Our objective is to perform zero-shot learning through modeling the relationship between seen classes y_1, \dots, y_p and unseen classes z_1, \dots, z_q . In this paper, we propose to use semantic graph to model the relationship among classes.

3.2 Semantic Graph

For measuring the relationship between two classes, we employ the word vector representation from the linguistic research [11, 12] and use the *cosine* similarity of their word vectors as the similarity measurement of the two classes.

Furthermore, a semantic graph is constructed as a k -nearest-neighbor graph. In the semantic graph, each class (regardless if it is a seen or unseen class) will have a corresponding graph node which is connected with its k most similar (semantically related) other classes. The edge weight w_{ij} of the semantic graph is the *cosine* similarity between two end node of this edge. More details about the semantic graph construction can be found in Section 4.1. After constructing the semantic graph, the graph structure will be fixed in the next steps of the pipeline.

We then define a special absorbing Markov chain process on the semantic graph, in which each unseen class node is viewed as an *absorbing* state and each seen class node is viewed as *transient* state. The transition probability from class node i to class node j is $p_{ij} = w_{ij} / \sum_j w_{ij}$, i.e. the normalized similarity. The absorbing state means that for each unseen class node i , we have $p_{ii} = 1$ and $p_{ij} = 0$ for $i \neq j$. It should be noted that since all of the unseen class nodes are absorbing states, there will have no *direct* connection between two unseen class nodes. In other words, the unseen classes will be connected through the seen classes.

We re-number the class nodes (states in Markov process) so that the seen class nodes (transient states) come first. Then, the transition matrix P of the above absorbing Markov chain process will

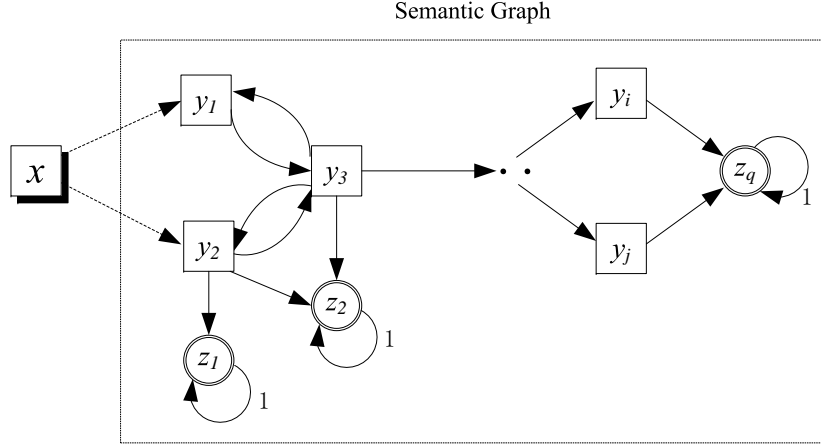


Figure 2: After incorporating the test image into the semantic graph, zero-shot learning can be viewed as an absorbing Markov chain process on semantic graph.

have the following canonical form:

$$P = \left(\begin{array}{c|c} Q_{p \times p} & R_{p \times q} \\ \hline \mathbf{0}_{q \times p} & I_{q \times q} \end{array} \right). \quad (1)$$

In El. 1, $Q_{p \times p}$ describes the probability of transitioning from a transient state (seen class) to another and $R_{p \times q}$ describes the probability of transitioning from a transient state (seen class) to an absorbing state (unseen class). In addition, $\mathbf{0}_{q \times p}$ and the identity matrix $I_{q \times q}$ mean that the absorbing Markov chain process cannot leave the absorbing states once it arrives.

3.3 Zero-shot Learning

For zero-shot learning, i.e. predicting the label of an unseen image x_i , we first need to incorporate x_i into the semantic graph. And then we will apply an extended absorbing Markov chain process, in which the test image x_i is involved, to perform the zero-shot learning.

In order to introduce a test image x_i into the semantic graph, it is connected with some seen class nodes¹. The nodes selected for connection is determined by the posterior probability $p(y_j|x_i)$ of image x_i belonging to seen class y_j . Specifically, the node representing image x_i is connected to the seen classes with the highest posterior probability, i.e. most visually similar. Note that for x_i , there will have no stepping in probabilities and the Markov process can only step out from x_i to other seen class nodes. The stepping out probabilities from x_i to seen class nodes are $t_{i,\cdot}$, which are the posterior probability computed using the seen class classifier as described in Section 3.1. x_i is thus incorporated into the semantic graph as a transient state. The transition matrix \tilde{P} of the extended absorbing Markov chain process have the following canonical form:

$$\tilde{P} = \left(\begin{array}{cc|c} Q_{p \times p} & \mathbf{0}_{p \times 1} & R_{p \times q} \\ \hline (t_{i,\cdot})_{1 \times p} & \mathbf{0}_{1 \times 1} & \mathbf{0}_{1 \times q} \\ \hline \mathbf{0}_{q \times (p+1)} & & I_{q \times q} \end{array} \right). \quad (2)$$

In the meanwhile, the extended transition matrix within all transient states, including all seen class nodes and one extra test image node x_i , are written as

$$\tilde{Q}_{(p+1) \times (p+1)} = \left(\begin{array}{c|c} Q_{p \times p} & \mathbf{0}_{p \times 1} \\ \hline (t_{i,\cdot})_{1 \times p} & \mathbf{0}_{1 \times 1} \end{array} \right), \quad (3)$$

¹Obviously it cannot be connected to the unseen class nodes directly as we are not mapping x_i in to the same semantic space.

and the extended transition matrix between transient states and absorbing states should be

$$\tilde{R}_{(p+1) \times q} = \begin{pmatrix} R_{p \times q} \\ \mathbf{0}_{1 \times q} \end{pmatrix}. \quad (4)$$

In the extended semantic graph, it is obvious that if there are many short paths that connect the test image node x_i and one unseen class node, e.g. z_j , the absorbing Markov chain process that starts from x_i will have a high probability to be absorbed at z_j . Thus, the probability that x_i is labeled as z_j should be high. This is a cumulative process and can be reflected by the absorbing probabilities from x_i to all unseen class nodes.

The absorbing probability b_{ij} is the probability that the absorbing Markov chain will be absorbed in the absorbing state s_j if it starts from the transient state s_i . The absorbing probability matrix $\tilde{B} = [b_{ij}]_{(p+1) \times q}$ can be computed as follows:

$$\tilde{B} = \tilde{N} \times \tilde{R}, \quad (5)$$

in which \tilde{N} is the fundamental matrix of the extended absorbing Markov chain process and is defined as follows:

$$\tilde{N}_{(p+1) \times (p+1)} = (\mathbf{I} - \tilde{Q})^{-1} = \begin{pmatrix} \mathbf{I}_{p \times p} - Q_{p \times p} & \mathbf{0}_{p \times 1} \\ -(t_{i,\cdot})_{1 \times p} & 1 \end{pmatrix}^{-1}. \quad (6)$$

We use the following block matrix inversion formula to compute \tilde{N} .

$$\begin{pmatrix} A & B \\ C & D \end{pmatrix}^{-1} = \begin{pmatrix} (A - BD^{-1}C)^{-1} & -(A - BD^{-1}C)^{-1}BD^{-1} \\ -(D - CA^{-1}B)^{-1}CA^{-1} & (D - CA^{-1}B)^{-1} \end{pmatrix}.$$

Since we only care about the absorbing probabilities that the absorbing chain process starts from the test image node x_i , we only need to compute the last row of \tilde{B} , i.e. $\tilde{B}_{p+1,\cdot}$ for x_i (x_i corresponds to the last transient state in the extended canonical form in Eq. 2). In particular, we can apply the above block matrix inversion formula to compute the last row of \tilde{N} as

$$\tilde{N}_{(p+1),\cdot} = \begin{pmatrix} (t_{i,\cdot})(\mathbf{I} - Q)^{-1}, & 1 \end{pmatrix}_{1 \times (p+1)} \quad (7)$$

and then we may further compute $\tilde{B}_{p+1,\cdot}$ as

$$\tilde{B}_{p+1,\cdot} = (\tilde{N}_{(p+1),\cdot}) \times \tilde{R} = (t_{i,\cdot})(\mathbf{I} - Q)^{-1}R. \quad (8)$$

For the whole test dataset with n images, we use a matrix $S_{n \times q}$ to store the computed absorbing probabilities, in which the i -th row $S_{i,\cdot}$ of S equals to the absorbing probabilities of x_i . If we stack the results of all test images together, we will get the final matrix S as follows,

$$S = T(\mathbf{I} - Q)^{-1}R. \quad (9)$$

In Eq. 9, T is a $n \times p$ matrix and $(\mathbf{I} - Q)^{-1}R$ is a $p \times q$ matrix that is only related to the semantic graph structure and can be pre-computed. The only dimension variable in Eq. 9 is the number of test images n . Therefore, our method is linearly with respect to the number of test images.

Finally, for the test image x_i , we assign it to the unseen label that has the maximum absorbing probability when the absorbing chain starts from x_i . That is,

$$f(x_i) = \arg \max_j S_{i,j} \quad (10)$$

It should be noted that in our formulation, we consider all the paths in the semantic graph, i.e. the whole structure of the semantic graph. Therefore, our method is more stable compared to direct similarity-based zero-shot learning, in the sense of being less sensitive to the number of connections to the seen classes for each test image, and the imperfect seen class classifier causing noise in the posterior probability computed. This is verified by the experimental results in Section 4.2.

Methods	Area under ROC curve (AUC) in %										mean AUC (in %)	mean accuracy (in %)
	chimpanzee	giant panda	leopard	Persian cat	pig	hippopotamus	humpback whale	raccoon	rat	seal		
direct-similarity [17]	76	73	84	78	76	78	98	73	82	77	79.7	39.8
ConSE [13]	76	49	85	71	71	65	99	72	81	72	74.1	35.1
SVR+NN	86	63	80	87	73	75	99	75	87	74	80.0	33.4
Our method	88	58	77	87	71	78	99	82	87	72	79.8	43.1

Table 1: Zero-shot classification results on the AwA dataset [10]. The best results per table column are indicated in bold.

4 Experiments

4.1 Experimental Setup

Dataset. We utilize the AwA (animals with attributes) dataset [9] to evaluate the performance of the proposed zero-shot learning method. AwA provides 50 classes of animals (30475 images) and 85 associated class-level attributes (such as furry, and hasClaws). In this work, attributes are not used unless otherwise stated. AwA also provides a defined source/target split for zero-shot learning with 10 classes and 6180 images held out.

Competitors. Our method is compared against three alternatives. The first two are the most related, namely Rohrbach et al.’s direct similarity-based ZSL (DS-based) [17] and Norouzi et al.’s convex semantic embedding ZSL (ConSE) [13]. Both methods take a semantic relatedness strategy and learn a n-way probabilistic classifier for the seen classes. In DS-based zero-shot learning, the semantic relatedness among categories are modeled as a bipartite graph. ConSE will choose the top K similar seen classes for a test image using the trained classifier, and then use the prototypes of the seen classes in the word space to form a new word vector for the test image. Zero-shot learning is performed by finding the most similar unseen prototype in the word space. In addition, we also apply the support vector regression to train a mapping from visual space to word space and after mapping each test image into the word space, the nearest-neighbor classifier is used to perform zero-shot learning. We call this direct mapping based method SVR+NN. This method differs from the other two and ours in that it uses the training data of seen classes to learn a mapping function rather than a classifier. Apart from these three, we also compare with the published results using attribute space rather than the semantic word space.

Settings. We first exploit the word space representation [12, 11] to transform each AwA seen or unseen class name to a vector in the word space. For the word space, we train the skip-gram text model on a corpus of 4.6M Wikipedia documents to form a 1000-D word space. Since the *seal* unseen class name of AwA has many meanings in English, not just the animal seal, we choose seven concrete seal species from the ‘seals-world’ website², that is, leopard seal, harp seal, harbour seal, gray seal, elephant seal, weddell seal and monk seal, to generate word vector for unseen *seal* class. We use the decaf feature [3] that is provided at the AwA website³ and apply the libsvm [2] to train a linear kernel SVM with probability estimates output. All other parameters in libsvm are set to the default value. For training SVR mapping, we apply the liblinear toolbox [4] and set the parameter $C = 10$. For semantic graph construction, we choose different k for seen classes and unseen classes when searching for the k -nearest-neighbors. That is, we first construct a subgraph with seen classes, in which we choose $k = 2$. For the similarity matrix W of the seen subgraph, we

²<http://www.seals-world.com/seal-species/>

³<http://attributes.kyb.tuebingen.mpg.de/>

Approach	semantic space	mean accuracy (in %)
DAP	attribute	40.5([10]) / 41.4([9])
IAP	attribute	27.8([10]) / 42.2([9])
ALE/HLE/AHLE [1]	attribute	37.4 / 39.0 / 43.5
Our method	word vector / attribute	43.1 / 49.5

Table 2: Comparison with the state-of-the-art attribute-based zero-shot learning on AwA.

set $W = (W + W^T)/2$ to ensure that it is symmetric for the seen classes. For each unseen class, we connect it with top $k = 4$ similar seen classes according to the cosine similarity in the word space. This will ensure that each unseen class is connected into the seen subgraph and there is no isolated unseen class node on semantic graph. The code of our method can be found at ⁴.

4.2 Results

Table 1 compare the zero-shot classification performance measure by area under ROC curve (AUC) scores for the ten individual test classes and their average. The last column in Table 1 gives the corresponding average multi-class classification accuracies. In DS-ZSL, ConSE and our method, each test image will be connected with $K = 5$ seen classes. From Table 1, we can see that the proposed semantic graph based method can achieve the best AUC results at six individual test classes and the best average multi-class classification accuracy. As for the average AUC on the ten test classes, the results of direct similarity-based method, SVR+NN and our method are almost the same. SVR+NN achieves the best average AUC result, but its average multi-class classification accuracy is the lowest.

Comparison with attribute-based ZSL. We also compare our result with the state-of-the-art results of attribute-based ZSL methods, including Lampert et al.’s DAP and IAP [9] and Akata et al.’s label-embedding method [1], on the AwA dataset. We list the results of average multi-class classification accuracy in Table 4.2. Overall, compared to the state-of-the-art attribute-based ZSL, our proposed method achieves better or comparable performance, especially compared to DAP and IAP. It should be noted that all the attribute-based ZSL methods are based on the well-defined visual attribute and the category-attribute relationship. In contrast, our method does not depend on manually defined visual attributes; instead we only exploit ‘free’ semantic word space learned from linguistic knowledge bases without the need for any manual annotation for the AwA classes. This is thus a very encouraging result. If we apply the given visual attributes on AwA to do the similarity computation, we can get 49.5% performance, which is much higher than the existing attribute-based methods.

Parameter sensitivity. Since DS-ZSL, ConSE and our method have a same parameter K , i.e., the number of top similar seen classes that a test image will choose, we analyze the effect of setting different values of K for the three methods. From Fig. 3, we can see that DS-ZSL will be heavily affected by the number of seen classes that connect with the test image, while ConSE and our method are more stable. Especially, our method is almost not influenced by the parameter K at all. That is because through the more robust semantic graph, our method can reduce the influence of the noisy seen classes which will be inevitably included when the value of K increases.

Running time comparison. We also test the running time of DS-ZSL, ConSE and our method w.r.t. different number of test images. There are totally 6180 test images on AwA. They are divided into 10 folds and we test increasing number of folds of test images, i.e. from 618 to 6180 and show the results in Fig. 4. We run each algorithm 100 times at a PC machine with 3.9GHz and 16GB memory and report the average result. From Fig. 4, we can see that all the three methods are linear and our method is significantly faster than the other two, especially given large number of test images.

5 Conclusion

In this work, we have introduced a novel zero-shot learning framework based on semantic graph. The proposed method models the relationship among visual categories using the semantic graph

⁴<https://sites.google.com/site/zhenyongfu10/>

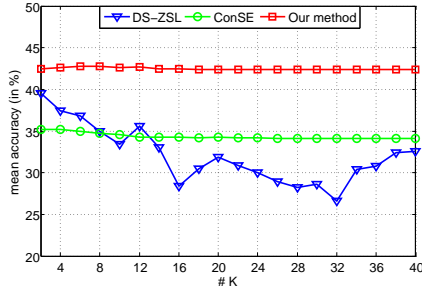


Figure 3: The performance (average multi-class classification accuracy in %) of DS-ZSL, ConSE and our method with respect to different settings of the parameter K .

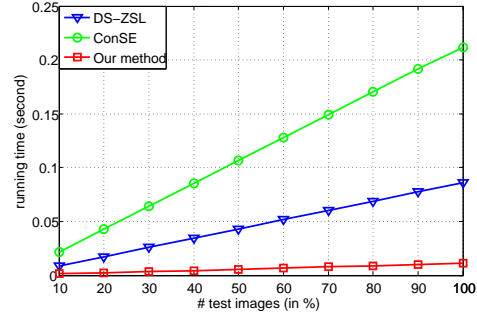


Figure 4: The running time of DS-ZSL, ConSE and our method with respect to different numbers of test images.

and then performs zero-shot learning through an absorbing Markov chain process on the semantic graph. We have shown experimentally that our method is more effective and more stable than the alternative bipartite graph based methods.

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